Specific abilities may increment psychometric *g* for high ability populations

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Abstract

Spearman's Law of Diminishing Returns (SLODR) postulates that correlations among cognitive ability tests are lower for higher ability groups, yet higher for low-ability groups. SLODR also suggests that specific ability tests are most likely to add incrementally beyond general cognitive ability to the prediction of performance for high-ability occupations. Results demonstrated that the Cyber Knowledge test added incremental prediction to general cognitive ability and the primary cognitive group factors against key criteria for high-ability soldiers assigned to cyber occupations. These criteria include training performance ratings and in person-job fit outcomes.

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14. ABSTRACT

Spearman's Law of Diminishing Returns (SLODR) postulates that correlations among cognitive ability tests are lower for higher ability groups, yet higher for low-ability groups. SLODR also suggests that specific ability tests are most likely to add incrementally beyond general cognitive ability to the prediction of performance for high-ability occupations. Results demonstrated that the Cyber Knowledge test added incremental prediction to general cognitive ability and the primary cognitive group factors against key criteria for high-ability soldiers assigned to cyber occupations. These criteria include training performance ratings and in person-job fit outcomes. Includes PowerPoint poster presentation (1 slide). Presented at 2016 SIOP Conference in Anaheim, California, April 14-16, 2016.

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The psychological construct of general mental ability was first introduced by Charles Spearman (1904). Spearman may be best known for his observation that cognitive ability tests are usually intercorrelated at modest levels and strong predictors of school performance. It is now widely accepted that general cognitive ability (i.e., Psychometric *g*) is an excellent predictor of school and job performance (e.g., Herrnstein & Murray, 1994; Hunter & Schmidt, 1996; Jensen, 1980). It is also widely accepted that the factoring of cognitive ability batteries yields primary group factors that are highly *g*-loaded (Carroll, 1993).

Using military data, Ree and Earles (1991) analyzed cognitive ability and school performance data for 78,000 air force enlistees assigned to 82 jobs. Their results showed that: (1) Psychometric *g* was an excellent predictor of school performance; (2) primary group factors (i.e., *G-Quantitative, G-Technical, G-Speed,* and *G-Verbal*) accounted for minor incremental variance beyond Psychometric *g*; and (3) specific ability tests added little to the prediction of school performance beyond Psychometric *g* and the primary group factors. These results suggest that attempts to augment general cognitive ability with specific cognitive ability tests will not be successful for most occupations.

Less well known is Spearman's observation that cognitive ability tests tend to be highly correlated in low ability groups, but less correlated in high ability groups (1927). This phenomenon has been replicated for a variety of cognitive ability test batteries (Detterman & Daniel, 1989; Lynn, 1990; Legree, Pifer & Grafton, 1996; Deary et al., 1996; Jensen, 2003; Hartmann & Nyborg, 2004; Nijenhuis & Hartmann, 2006). These analyses also show that cognitive ability tests and primary group factors extracted from those tests are less g-loaded in higher ability subgroups (Legree, Pifer & Grafton, 1996). Spearman's Law of Diminishing Returns (SLODR) encapsulates the general finding that correlations among cognitive ability tests are lower for higher ability groups.

SLODR effects can be surprisingly large. For example, Jensen (2003) reported the mean correlation among the WAIS subtests as .43 for below average adults, but only .18 for above average adults. Similar results have been reported for the Armed Services Vocational Aptitude Battery (ASVAB; Legree, Pifer & Grafton, 1996). The magnitude of these SLODR effects suggest that specific ability tests will be most likely to provide incremental validity beyond Psychometric *g* for high-ability populations because they are less *g*-loaded for high ability populations.

Current Application

All enlisted soldiers complete the Armed Services Vocational Aptitude Battery (ASVAB) prior to joining the U.S. Army. The ASVAB contains nine cognitive tests that are named for their content: Word Knowledge (WK), Paragraph Comprehension (PC), General Science (GS), Math Knowledge (MK), Arithmetic Reasoning (AR), Electronics Information (EI), Auto Shop (AS), Assembling Objects (AO) and Mechanical Comprehension (MC). Performance on ASVAB tests is used to assign recruits to occupations as they enlist in the U.S. Army.

In recent years, the military has become highly focused on the identification of individuals who are most likely to excel in the cyber domain. Currently, soldiers must have above average ASVAB scores in order to join cyber occupations: In terms of population norms, the minimal acceptable score is at the 69th percentile of general mental ability. In this project, we evaluated the utility of a new cognitive test that was designed to assess Cyber Knowledge (CK) in this occupation. The CK test is a knowledge-based measure designed to screen entry-level Military personnel's potential to succeed in cyber jobs.

Hypotheses

Because cyber soldiers represent an above average ability group and based on our understanding of SLODR, we propose the following hypotheses:

H1: The CK test will explain incremental variance in training performance ratings of above and beyond *g*.

H2: The CK test will explain incremental variance in training performance ratings above and beyond the ASVAB primary group factors: *Technical, Quantitative,* and *Verbal.*

To further test the incremental validity of specific abilities in explaining outcome variance above and beyond that of both Psychometric *g* and the primary group factors, we included a second outcome variable, person-job fit. Although traditional studies concerning the incremental validity of specific abilities have focused on training and performance outcomes (e.g., Thurstone, 1938; Hull, 1928; Ghiselli, 1973, Hunter, 1986), we include job fit because it is related to cognitive ability in cyber occupations due to the high standards for entry. In addition, the Gravitational hypothesis states that individuals will tend to sort themselves into jobs that are commensurate with their ability level (McCormick, DeNisi, & Staw, 1979; McCormick, Jeanneret, & Mecham, 1972), and this hypothesis has received empirical support (Wilk & Sackett, 1996). Therefore, it follows that in occupations that require higher cognitive ability (e.g., cyber occupations), higher ability individuals will tend to have a better fit with that job. Including person-job fit as a second outcome variable also serves as a test of the boundaries in which specific abilities have incremental validity in explaining criterion variables (i.e., can specific abilities explain more than test scores and job performance?) Therefore, we propose the following:

H3: The CK test will explain incremental variance in person-job fit above and beyond *g*.

H4: The CK test will explain incremental variance in person-job fit above and beyond the ASVAB primary group factors: *Technical, Quantitative,* and *Verbal.*

We also emphasize that these hypotheses contrast with more general guidance that specific cognitive ability tests are unlikely to account for little variance against work-related outcomes beyond general cognitive ability and the primary group factors (Schmidt & Hunter, 1977; Ree & Earles, 1991.)

Method

Participants

Data were obtained from an Army database containing a sample of 1092 soldiers, which were assigned to Information Technology Specialist occupations: 561 (51.4%) had high school degrees, 359 (32.9%) had some college, and 43 (3.9%) percent had college degrees, and 78 (7.1%) reported a higher education level. The average Army Physical Fitness Test (APFT) self-reported score was M=231.02 (SD=38.96). The average ASVAB skilled-technical (ST) composite score for this sample is M=108.16 (SD=10.98).

Measures

ASVAB. The ASVAB is a cognitive ability test that is required for all personnel who want to join any of the Military services. Data for soldiers' ASVAB test scores were obtained from an Army database. We computed general and group factor scores (i.e., *Psychometric g, G-Verbal, G-Quantitative,* and *G-Technical*) using the procedure recommended by Jensen and Weng (1994).

Cyber Knowledge Test (CT). The CK test contains 29 items that measure the following content areas: Information Technology Software/Tools and Personal Computer Configuration and Maintenance; Networking and Communications; Security and Compliance; Software Programming; and Web Development. CK test scores are scaled to range between 0 and 79 with higher scores reflecting higher levels of cyber knowledge.

Training Performance Evaluations. At the end of training, peers of soldiers were randomly assigned to groups ranging between four and six soldiers. Each soldier was asked to rate the performance of each of the soldiers in their group on six different competencies: implement network, hardware concepts, software applications, network security, troubleshooting, and safety. Ratings ranged from 1 (poor performance) to 5 (outstanding performance).

Procedure

We administer the CK test to a random sample of soldiers who were assigned to the Information Technology occupation prior to those individuals completing the required cyber training course. The test required approximately 20 minutes to complete. Soldiers who participated also consented to allowing their ASVAB scores to be obtained from an Army database.

Results

Preliminary Analyses and Descriptive Statistics

All data were analyzed using SPSS 21. We factored the ASVAB using the procedure recommended by Jensen and Weng (1994). Initially a principal axis oblique rotation factor analysis was run on the nine ASVAB test scores (GS, AR, WK, PC, MK, EI, AS, MC, and AO). Using the Kaiser rule, three factors were extracted. The pattern matrix is presented in Table 1. The AS, MC, EI, and AO tests loaded on factor 1, which we interpret as a *Technical factor*. The MK and AR tests loaded on a factor 2, which we interpret as the *Quantitative factor*. The WK, GS, and PC tests loaded on the third factor were, which represents the *Verbal factor*.

A principle components factor analysis was run on these three factors, and a single component was extracted. Table 2 reports primary factor loadings on the high-order factor. This factor represents *Psychometric g*. All factor scores were computed and saved using the regression method.

It is worth noting that within this high ability sample, the correlations between the three group factors were relatively lower than what might be expected in a lower ability sample (cf. Legree, Pifer & Grafton, 1996). The *Technical* and *Quantitative* factors correlated $r = .35$, $p < .001$. The *Technical* and *Verbal* factors correlated $r = .64$, $p < .001$. Finally, the *Quantitative* and *Verbal* factors correlated $r = .46$, $p < .001$.

Regression Analyses

A stepwise multiple regression analyses was run to test Hypothesis 1, which postulates the CK test adds incremental validity over and above *g* against the training performance criterion. Accordingly, the Psychometric *g* scores were entered in the first step of a stepwise multiple regression analysis, and CK test scores were entered into the second step. Training performance ratings was the dependent variable. Psychometric *g* accounted for 10.9% of the variance in the training performance ratings. After adding the Cyber Test scores in step 2, R^2 increased from .109 to .133, which represents a statistically significant increase in the proportion of variance in training performance explained by the Cyber Test scores, ΔR^2.= .024, $F(1,1039) = 29.26$, $p < .001$. This increase also represents a 22 percent gain in the proportion of variance accounted for in cyber ratings by adding the CK test to psychometric *g*. Results are detailed in Table 3.

A stepwise multiple regression analyses was run to test Hypothesis 2, which postulates the CK test adds incremental validity over and above the ASVAB Group factors against the training performance criterion. Accordingly, the *Technical, Quantitative, and Verbal* factors were entered in the first step. Then cyber test scores were entered in the second step. The dependent variable was the training performance evaluations. The three group factors accounted for 11.6% of the variance in the training performance ratings. After adding the Cyber Test scores in step 2, R^2 increased from .114 to .141, which represents a statistically significant increase in the proportion of variance in training performance ratings explained, $\Delta R^2 = .028$, $F(1,1037) = 33.58$, $p < .001$. This increase represents a 24 percent gain in the proportion of variance accounted for in cyber ratings by adding the CK test to psychometric *g*. Results are shown in Table 4.

A stepwise multiple regression analyses was run to test Hypothesis 3, which postulates the CK test adds incremental validity over and above *g* against the job fit criterion. Accordingly, the psychometric *g* scores were entered into the first step of a stepwise multiple regression analysis, and CK test scores were entered into the second step. Self-reported job fit was the dependent variable. The g measure accounted for

5.7% of the variance in job fit. After adding the Cyber Test scores in step 2, R^2 increased from .057 to .091, which represents a statistically significant increase in the proportion of variance in job fit explained by the Cyber Test scores, ΔR^2.= .034, $F(1,892) = 33.31$, $p < .001$. This increase also represents a 60 percent gain in the proportion of variance accounted for in job fit by adding the CK test to psychometric *g*. Results are detailed in Table 5.

A stepwise multiple regression analyses was run to test Hypothesis 4, which postulates the CK test adds incremental validity over and above the ASVAB Group factors against the job fit criterion. Accordingly, the *Technical, Quantitative, and Verbal* factors were entered in the first step. Then cyber test scores were entered into the second step. The dependent variable was self-reported job fit. The three group factors accounted for 5.8% of the variance in job fit. After adding the Cyber Test scores in step 2, R^2 increased from .058 to .092, which represents a statistically significant increase in the proportion of variance in job fit explained, $\Delta R^2 = .033$, $F(1,890) = 32.62$, $p < .001$. This increase also represents a 59 percent gain in the proportion of variance accounted for in job fit by adding the CK test to psychometric *g*. Results are shown in Table 6.

Discussion

Based on our understandings of SLODR, we proposed that a specific cognitive ability test would add incremental prediction to the primary and secondary factors against both training performance and person-job fit criteria for a high-ability population. Our results demonstrated strong support for our hypotheses. A 22 percent gain in the proportion of variance accounted for in training performance ratings was found by adding CK to Psychometric *g*, while a 24 percent gain was found after adding CK to the ASVAB primary factors. In addition, a 60 percent gain in the proportion of variance accounted for in person-job fit was found by adding CK in addition to psychometric *g*, while a 59 percent gain was found after adding CK in addition to the ASVAB Group factors.

These results provide support for the use of specific ability tests in addition to Psychometric *g* and the primary factors to predict the performance of high ability individuals. Our results are also consistent with SLODR findings because the ASVAB primary factor correlations were lower for this high-ability sample than would be expected for factor correlations computed using lower ability groups. These results suggest that the answer to the general question “Do specific abilities add to *g*?” appear to be “It depends.” Specifically, it depends on whether the group in question is of high or low ability. These results indicate that specific cognitive ability tests are most likely to add incremental predictive validity against important workplace outcomes for those occupations that are staffed by higher-than-average ability groups.

Therefore, test developers should consider the type of population to which their assessments will be administered, and be aware of the increase in validity that may be obtained by including specific ability tests in situations in which the target population is of higher cognitive ability. A well-known example of such a situation is that of graduate school admissions requirements. It is typically the case that the more competitive programs require applicants to take the subject-specific GRE along with the general GRE. Given the presence of SLODR, this approach is sensible because the more competitive programs are drawing the most intelligent individuals (among whom the SLODR effect is likely to be found). Therefore, the specific ability tests (i.e., subject-specific GRE tests) are likely to add predictive validity above general ability tests (i.e., the general GRE).

Our results may appear to contradict much research suggesting that specific ability tests add little or no validity beyond Psychometric *g* and the primary cognitive group factors in predicting work outcomes (Schmidt & Hunter, 1977; Ree & Earles, 1991). However, we do not dispute that specific tests often add little variance beyond Psychometric *g* and the group factors for most applications and especially for those applications that are not associated with high ability groups of individuals.

In our opinion, a more practical research goal is to identify the conditions under which specific tests are most likely to add incrementally to general cognitive ability. This information could then be used to identify applications for which specific tests are most likely to add incremental validity.

We believe these applications will often correspond to critical occupations for which high levels of performance are required (e.g., cyber security) and for which high ability individuals are often sought. In a general way, this result suggests that the future of specific ability tests will lie in their application to improve the selection and classification of personnel for complex occupations where high levels of performance is critical.

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Table 1. Pattern Matrix from the Oblique Rotation, Principal Axis Factor Analysis of the ASVAB test scores

ASVAB Test	Primary Factors		
	Quantitative	Technical	General Knowledge
Auto Shop (AS)	**.74**	-.17	.14
Mechanical Comprehension (MC)	**.61**	.14	.24
Electronic Information (EI)	**.58**	-.01	**.34**
Assembling Objects (AO)	**.32**	.06	-.08
Math Knowledge (MK)	-.08	**.79**	.03
Arithmetic Reasoning (AR)	.17	**.70**	.08
Word Knowledge (WK)	.02	-.04	**.77**
General Science (GS)	.18	.08	**.65**
Paragraph Comprehension (PC)	-.05	.13	**.63**

Table 2. Group factor loadings on a single *g* factor.

Group Factors	Psychometric *g*
General Knowledge	-.88
Technical	.83
Quantitative	.71

Table 3. Training Ratings: Incremental validity of the Cyber Test above and beyond psychometric *g*.

Model	R	R^2	Adj R^2	Std Error	Model Change Statistics				
					R^2	F	df1	df2	Sig. F
1	.33	.11	.11	.74	.11	127.30	1	1040	.000
2	.37	.13	.13	.73	.02	29.26	1	1039	.000

Table 4. Training Ratings: Incremental validity of the Cyber Test above and beyond the three group factors.

Model	R	R^2	Adj R^2	Std Error	Model Change Statistics				
					R^2	F	df1	df2	Sig. F
1	.34	.12	.11	.74	.12	45.60	3	1038	.000
2	.38	.14	.14	.73	.03	33.58	1	1037	.000

Table 5. Incremental validity of the Cyber Test above and beyond psychometric *g* (DV = job fit).

Model	R	R^2	Adj R^2	Std Error	Model Change Statistics				
					R^2	F	df1	df2	Sig. F
1	.24	.06	.06	.74	.06	53.71	1	893	.000
2	.30	.09	.09	.72	.03	33.31	1	892	.000

Table 6. Incremental validity of the Cyber Test above and beyond the three group factors (DV = training performance ratings).

Model	R	R^2	Adj R^2	Std Error	Model Change Statistics				
					R^2	F	df1	df2	Sig. F
1	.24	.06	.06	.74	.06	18.41	3	891	.000
2	.30	.09	.09	.72	.03	32.62	1	890	.000

Specific Abilities May Increment Psychometric *g* for High Ability Populations

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Abstract

Spearman's Law of Diminishing Returns (SLODR):

1. **Postulates that correlations among cognitive ability tests are lower for higher ability groups, yet higher for low-ability groups.**
2. **Predicts that specific ability tests are most likely to add incrementally beyond general cognitive ability to the prediction of performance for high-ability occupations.**

Analyses demonstrate that the Cyber Knowledge Test added incremental prediction to general cognitive ability and the primary cognitive group factors against work-related criteria for a high-ability occupation.

Introduction

- Charles Spearman (1904) introduced the psychological construct of general mental ability.
  - Subsequent analyses indicate that attempts to augment general cognitive ability with specific cognitive ability tests will not be successful for most occupations (Hunter 1986; Ree & Earles, 1991).
- Spearman (1927) observed that cognitive ability tests tend to be highly correlated in low ability groups, but less correlated in high ability groups.
  - This result has been replicated for various cognitive ability test batteries (e.g., Detterman & Daniel, 1989; Lynn, 1990; Legree, Pifer & Grafton, 1996; Deary et al., 1996; Jensen, 2003; Hartmann & Nyborg, 2004; Nijenhuis & Hartmann, 2006).
  - Termed Spearman's Law of Diminishing Returns (SLODR).
- The Military has become focused on identifying talent to excel in the cyber domain.
  - Entry into cyber training courses requires a minimal acceptable score at the 69th percentile of general mental ability.
  - We evaluated the incremental utility of the Cyber Knowledge (CK) test to select individuals for this occupation (i.e., screen entry-level military personnel potential to succeed in cyber jobs).

Hypotheses

H1: The CK test will explain incremental variance in each of the criteria above and beyond *g*.

H2: The CK test will explain incremental variance in each of the criteria above and beyond the ASVAB primary group factors: *Technical, Quantitative,* and *Verbal*.

Outcome variables include training course grades, peer ratings of training performance, and a self-report measure of person-job fit.

Participants

Army data were obtained for 1092 soldiers who were assigned to Information Technology Specialist occupations: 561 (51.4%) had high school degrees, 359 (32.9%) had some college, and 43 (3.9%) percent had college degrees, and 78 (7.1%) reported a higher education level. The average ASVAB skilled-technical composite score for this sample is M = 108.16; SD = 10.98.

Measures

ASVAB. The ASVAB is a cognitive ability test that is required for all personnel who want to join any of the Military services. We computed general and group factor scores (i.e., *Psychometric g, G-Verbal, G-Quantitative,* and *G-Technical*) using the procedure recommended by Jensen and Weng (1994).

Cyber Knowledge Test (CT). The CK test contains 29 items that measure the following content areas: Information Technology Software/Tools and Personal Computer Configuration and Maintenance; Networking and Communications; Security and Compliance; Software Programming; and Web Development. CK test scores are scaled to range between 0 and 79 with higher scores reflecting higher levels of cyber knowledge.

Job Fit. Job fit (MOS fit) was measured using a six-item scale, which is part of the Army Life Questionnaire. Item responses ranged from 1 (strongly disagree) to 5 (strongly agree). A sample item is "I feel like I am part of the Army 'family.'"

Measures (cont.)

Training Performance Evaluations. At the end of training, peers of soldiers were randomly assigned to groups ranging between four and six soldiers. Each soldier was asked to rate the performance of each of the soldiers in their group on six different competencies: implement network, hardware concepts, software applications, network security, troubleshooting, and safety. Ratings ranged from 1 (poor performance) to 5 (outstanding performance).

Training Course Grades. End of training course grades were available for approximately half of the sample (N = 527). End of training course grades ranged between 35 and 100 percent with a mean of M = 81.78 (SD = 9.63).

Results

- We factored the ASVAB using procedure recommended by Jensen and Weng (1994). Initially a principal axis oblique rotation factor analysis was run on the nine ASVAB test scores (GS, AR, WK, PC, MK, EI, AS, MC, and AO). Using the Kaiser rule, three factors were extracted.
- Psychometric *g* was then extracted from the primary factors
- Used multiple regression analyses to test the two hypotheses for each of the three different outcomes.
- Results are summarized in Table 2. Findings show that both hypotheses 1 and 2 were supported for each of the outcome variables as predicted.

Table 1. Pattern Matrix from the Oblique Rotation, Principal Axis Factor Analysis of the ASVAB test scores

ASVAB Test	Primary Factors		
	Quantitative	Technical	General Knowledge
Auto Shop (AS)	**.74**	-.17	.14
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Electronic Information (EI)	**.58**	-.01	**.34**
Assembling Objects (AO)	**.32**	.06	-.08
Math Knowledge (MK)	-.08	**.79**	.03
Arithmetic Reasoning (AR)	.17	**.70**	.08
Word Knowledge (WK)	.02	-.04	**.77**
General Science (GS)	.18	.08	**.65**
Paragraph Comprehension (PC)	-.05	.13	**.63**

Results (cont.)

Table 2. Incremental Value of the Cyber Test (entered in Step 2)

Criterion	R Step 1	R Step 2	ΔR² Step 1 to 2	Change Statistics
Above and Beyond Psychometric *g* (entered in Step 1)				
Course Grades	.45	.48	.02	F (1, 521) = 16.45, p<.001
Peer Ratings	.33	.37	.02	F (1, 1038) =29.09, p<.001
Job Fit	.23	.30	.04	F (1, 973) = 39.27, p<.001
Above and Beyond the Three Primary Group Factors (entered in Step 1)				
Course Grades	.48	.50	.03	F (1, 519) = 19.04, p<.001
Peer Ratings	.34	.38	.03	F (1, 1036) = 33.43, p<.001
Job Fit	.23	.30	.04	F (1, 971) = 39.29, p<.001

Discussion

- These results indicate that specific cognitive ability tests may add incremental predictive validity against important workplace outcomes for occupations that are staffed by higher-than-average ability groups.
- Graduate admissions requirements are one such example. Due to the SLODR effect, the specific ability tests (i.e., subject-specific GRE tests) are likely to add predictive validity above general ability tests (i.e., the general GRE).
- A more practical research goal is to identify the conditions under which specific tests are most likely to add incrementally to general cognitive ability. This information could then be used to identify applications for which specific tests are most likely to add incremental validity.
- These results suggest that the future of specific ability tests will lie in their application to improve the selection and classification of personnel for complex occupations where high levels of performance is critical.